Spectral noise measurements supply instantaneous traffic information for multidisciplinary mobility and traffic related projects.

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ABSTRACT

The effect of traffic on health and quality of life is a multidisciplinary field which requires good knowledge of the driving force: the local traffic and traffic dynamics. The noise exposure is not only an important indicator for the health effects. The measured exposure can be used as instantaneous traffic information for the adjacent traffic related disciplines.
The noise measurements can be static (fixed network) or mobile (walking or biking). The spectral content in the noise measurements detects the local traffic dynamics and adds relevant information in a high temporal and spatial resolution. The technique is illustrated for the exposure to particulate matter (Black Carbon), an exposure measure with an extreme spatiotemporal variation. The instantaneous traffic assessments and quantification of the traffic dynamics enables the disentanglement of the variation due to local traffic counts, traffic dynamics, instantaneous meteorological influences and long-term changes in background exposure.
The integration of fixed noise measurement networks and continuous mobile noise sampling in multidisciplinary smart city setups quantifies the variability of traffic in an enhanced resolution in both space and time.

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1. INTRODUCTION

Individual mobility of people has grown considerably in the past decades, resulting in increasing traffic and an exponential increase of congestion. Mobility fulfills a daily needs through accessibility of the different functions (work, school, services, recreation, etc.)(1). The adverse impact of traffic includes direct exposures to noise and air pollution but goes beyond and also includes direct health impacts, social aspects such as walkability, subjective safety. The health impact of traffic is a complex multivariate and multidisciplinary problem affecting our daily life though a large set of direct and indirect pathways. Increased personal mobility is in itself also the main driving force of the interpersonal variability in the exposure. To assess this impact, the quality of indicator calculation, from individual vehicles emission over traffic flows and propagation up to the personal exposure is critical. Before the health pathways can be included in these indicators more precisely, the data quality of the driving force: the traffic flows and traffic dynamics, has to be improved.

The mobility research field is mainly focused on resolving the congestion issues and the effects on the economical function of traffic and hence focusses on obtaining high quality data for the main roads sensitive to congestion. On the smaller roads and off-peak, the quality of the data drops. Health impact analysis is a relative evaluation, comparing high exposed with low exposed, but the quality of the traffic data is unbalanced. High quality data is available for high exposed situation in space and time -close to major roads and highways during rush hour- while the data quality is poor for the low traffic roads and off-peak (night) situations. To make health impact assessment more precise, the first target

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should be improving the traffic data quality at expected low exposure conditions and by doing so, improve contrast and resolution in the health impact analyses.

In previous work, the broader picture of the impacts of traffic has be addressed through the Traffic Liveability, a traffic related portion of the Quality of Life assessments (1). It can be described through multiple indicators and fuzzy aggregation functions. The traffic information at low density roads is added to the model by simulating the population mobility behavior. The subjective Quality of Life correlates very well with local aspects of noise exposure since the subjective response to Quality of Life is well predicted by noise assessments at the dwelling facade (1). Subjective assessment of Traffic livability is not sensitive to the health effects of air pollution, yet health is an important factor in overall Quality of Life. Increased spatial resolution of the traffic assessments is expected to improve the exposure assessments to traffic related air pollution and as such will improve traffic livability and quality of life indicators. This is the basic hypothesis in the PhD of Luc Dekoninck (2).

An important part of the interpersonal variability is related to the personal time-activity pattern and the matching micro-environment (indoor, in-vehicle, bicycle…) (3-4). The goal of the PhD is to quantify the traffic and traffic dynamics through noise assessments at a spatial resolution in a similar resolution as the variability of the personal time activity pattern. The models are micro-environment specific and the traffic simulations are replaced by noise measurements to assess actual traffic in all it spatial and temporal variability. The variability of PM exposure is a combination of factors: local traffic and traffic dynamics, meteorology, background concentrations, stability of the atmosphere (boundary conditions), large scale in-city accumulation, seasonal aspects of different air pollution sources, changing emission characteristics at fleet level, particle dynamics etc. Instantaneous traffic assessment has the potential to assess the local variability and can be an important element in disentangling the variability in PM exposure in local components and large-scale components (2).

The technique is tested in two variants. Mobile measurements performed on a bicycle are used to evaluate and quantify the sensitivity of route choice and local traffic features. Fixed noise monitoring at dwelling facades are used to disentangle the long-term meteorological influences. Noise is a complex parameter due to the source specific temporal dynamics and spectral content. The spectral content reveals features of the noise source. In this paper, we will focus on the spectral components with the strongest relation with PM exposure. The simultaneous noise and air pollution measurements are evaluated up to a temporal resolution of seconds. Exposure prediction models for Black Carbon are presented with a focus on the use of spectral noise information as alternative traffic data.

2. MOBILE NOISE and AIR POLLUTION MEASUREMENTS

2.1 Engine and Rolling noise spectral content

The harmonized calculation method used for noise map calculations for the European Union (END Directive) separates the noise emission into an engine contribution and a rolling noise contribution. Engine noise contains predominantly low frequencies; rolling noise high frequencies. At low driving speeds, in particular for heavy vehicles, engine noise dominates, while at higher driving speeds rolling noise becomes the dominant source of road vehicle noise. The parameters used in the proposed analysis method are directly related to these emission features. The first parameter L_{OLF} is the energetic sum of the 100 – 200 Hz-bands (A-weighted) and describes the engine noise of the nearby traffic. High throttle increases the engine noise and thus on average dynamic traffic containing acceleration and deceleration epochs will result in higher values for L_{OLF}. L_{HLF} is the energetic sum of the 1000 – 2000 Hz bands and is related to the rolling noise. A relative parameter L_{HFmLF} is defined as the difference between L_{OHF} and L_{OLF} in the noise spectrum. High levels of L_{HFmLF} detect a relatively stronger contribution of high frequencies compared to low frequencies and indicate a stronger contribution of rolling noise due to the nearby traffic. This is typical traffic at higher speed (5). Figure 1 sketches two different traffic situations with similar overall noise levels (in dBA). The L_{OLF} and L_{HFmLF} describe the differences in the spectral content very efficient. L_{OLF} quantifies the amount of vehicles, the distance to the source and the engine regime in a single attribute. L_{HFmLF} expresses the speed of the traffic flow.

In mobile measurements on bicycles, these parameters are calculated in a one second resolution, a moderate smoothing function is applied (running smooth of 5 seconds). For modelling purposes, the parameters are averaged in a temporal resolution of 10 seconds. The typical speed of a bicyclist is 18 km/h. This results in a spatial resolution of 50 m along the trajectories.

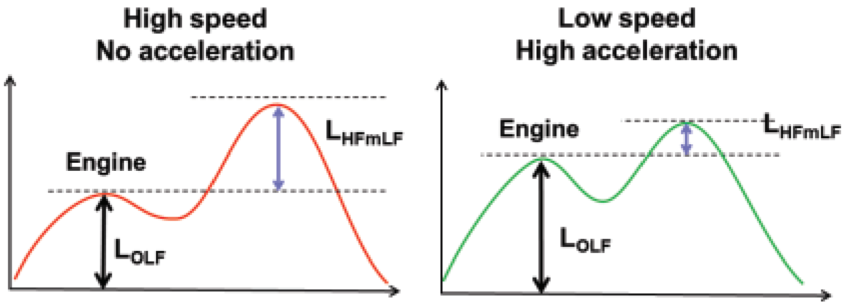

Figure 1 – Two different traffic situations with similar $L_{Aeq,1\ sec}$ noise levels can be distinguished by two noise parameters L_{OLF} and L_{HFmLF}.

2.2 Measurement campaigns

Two mobile measurement campaigns were performed. One measurement campaign covered a full year of measurements and meteorological conditions in and around the city of Ghent, Belgium (5). A second short campaign was performed in Bangalore, India to verify the international applicability (6). The measurements in Bangalore include also UFP particle counts.

In Figure 2, the spatial average of the mobile measurements in the city of Ghent (5) illustrates the differences and spatial variability of the two noise parameters. High levels of L_{OLF} indicate dense traffic or highly dynamic traffic. High levels of L_{HFmLF} indicate the road segments where traffic speed is high. Near the highway in the south-west of the map, the effect of noise screens and a partial elevated highway are visible in the noise measurements. The distance of the bicycle infrastructure to the closest traffic lane also explains part of the spatial variability.

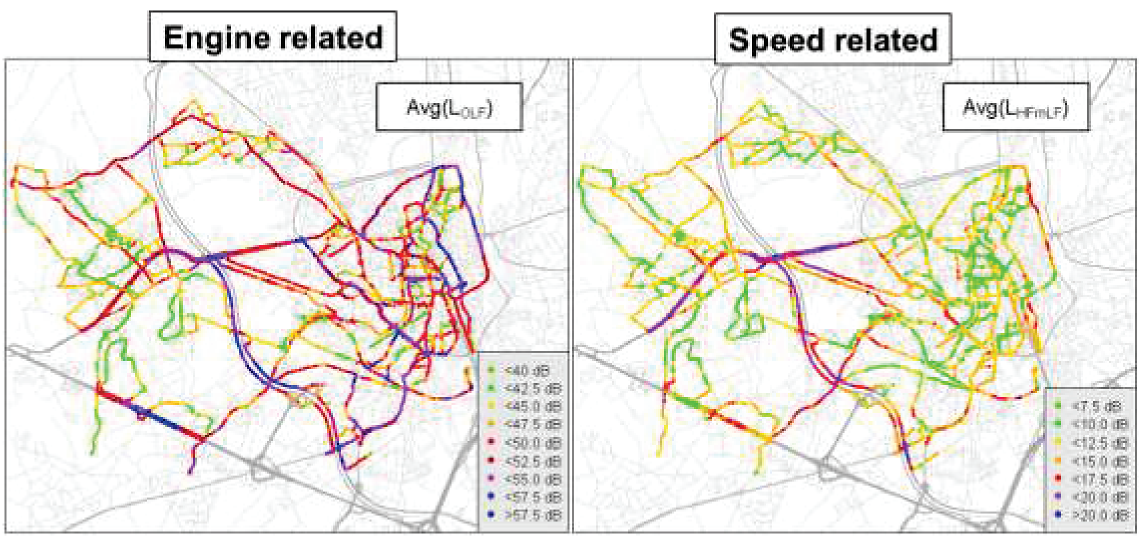

Figure 2 – Spatial average of the mobile noise measurements in the city of Ghent for L_{OLF} (engine related noise) and L_{HFmLF} (speed related noise).

2.3 Black Carbon instantaneous models

A prediction model for the exposure to Black Carbon is based on an additive approach (2, 5). The exposure is evaluated as the sum of a background component and a local component. The background component is retrieved from a continuous air pollution monitor of the Flemish Government.

$$BC_{raw,i,j} = BC_{loc,i,j} + (BC_{bkg,j} - Q1(BC_{bkg,lt})) \quad (1)$$

Non-linear modeling is included with Generalized Additive Models (GAMs), regression models where smoothing splines are used instead of linear coefficients for the covariates. This approach has been found to be particularly effective for handling the complex non-linearity associated with air pollution research. In Figure 3, the non-linear splines are shown for the four strongest covariates in a model for log(BC_{loc}). After adjusting for the background concentration (eq. 1) the engine noise is the strongest component. The strength of the wind speed covariate is reduced by the background adjustment but remains the second strongest covariate in the local component of the bicyclist's exposure (5). A parameter describing the buildup environment (Street Canyon Index) illustrates the effect of accumulation of pollution in narrow streets. The fourth parameter is the speed related parameter L_{HFmLF}. This clearly shows that at high speeds the Black Carbon exposure is not increasing with speed of the traffic. Since the L_{Aeq} is increasing with increasing speed, this identifies a breakdown of the correlation between overall noise exposure and Black Carbon exposure.

In literature, many investigators attempt to quantify the correlation between L_{Aeq} and particulate matter (PM) exposure (8, 9, 10, 11, 12, 13). Most of these attempts used measurement locations close to the highways where higher exposure levels are expected. The resulting correlations are mostly lower than expected. The presented model illustrates that the correlation fails when the rolling noise becomes dominant. It explains why the correlation between A-weighted overall noise level and PM concentrations close to highways is lower than expected. PM emissions are relatively lower since the highest PM emission occurs in dynamics traffic, not at constant high speeds on the highways. The total noise emission increases with speed, but the relative contribution of the engine noise drops, as do the PM emissions. The spectral evaluation improves the predictive quality of the model.

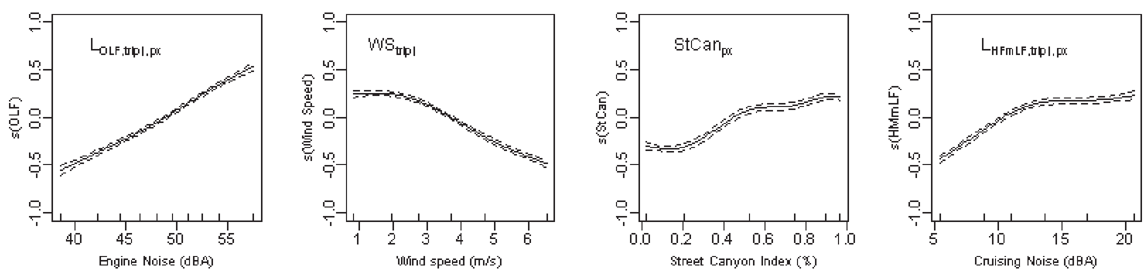

Figure 3 – GAM splines of the BC_{loc} model show the different relation between the engine related noise (L_{OLF}) and the speed related noise parameter (L_{HFmLF}).

2.4 Noise measurements quantify the driving force of local traffic related air pollution

In this section, the most important features of the mobile noise measurements are illustrated. These features result in a number of potential applications. First we address the power to resolve local traffic through noise exposure. The instantaneous model disentangles traffic and meteorological effects and enables the prediction of local BC exposure for any meteorological condition at all sampled locations. In a recent publication, this feature is used to calculate local yearly average exposure along the network [6]. One of the main results is the fast convergence of the technique. Only four passages are required to adequately predict the yearly local exposure to BC. Straight forward analysis of mobile air pollution measurements requires much large sample sets (14). Moreover, now the driving force of local BC exposure can be quantified in a very efficient way, scanning an entire city with mobile microphones results in a spatial resolution of traffic and traffic dynamics on all roads, including the low traffic density roads. Quantifying the traffic on low density roads results in better exposure estimates for alternative trajectories and gives the local governments a tool to advertise the benefits of alternative routes to cyclists. This could ultimately create policy support for investments in alternative bicycle infrastructure. A mobile app can disseminate the results to the bicyclist community and becomes a policy instrument to accelerate the shift from car use to more active transportation modes.

A mobile measurement campaign in Bangalore illustrated the applicability of the technique. The quality of the local model was hampered by high background concentrations levels. The background measurement location was placed inside the city. The local contribution of Black Carbon and UFP exposure in low density streets was much smaller than the background variation and the resulting models lacked sensitivity at low L_{OLF}. A pooled model, merging the data of the campaign in Ghent, Belgium and the data from Bangalore, India improved the sensitivity of the model for low traffic roads (7). Predicting the trip exposure in Bangalore with the pooled model improved the correlation significantly (Figure 4). The mobile noise measurements are low intensity roads are sensitive enough to provide local BC exposures estimates well below the highly variable levels of the background concentrations. At this point the features of the background measurement location become parameters that should be included into the model design. The modelling approach is also valid for UFP and spectral evaluation shows an even stronger non-linear log-log relation with UFP (7). The background variability of the UFP concentrations is in relative terms, lower compared to the variability in the BC background concentrations. The UFP model is therefore less sensitive to features of the background locations and more sensitive to the traffic dynamics.

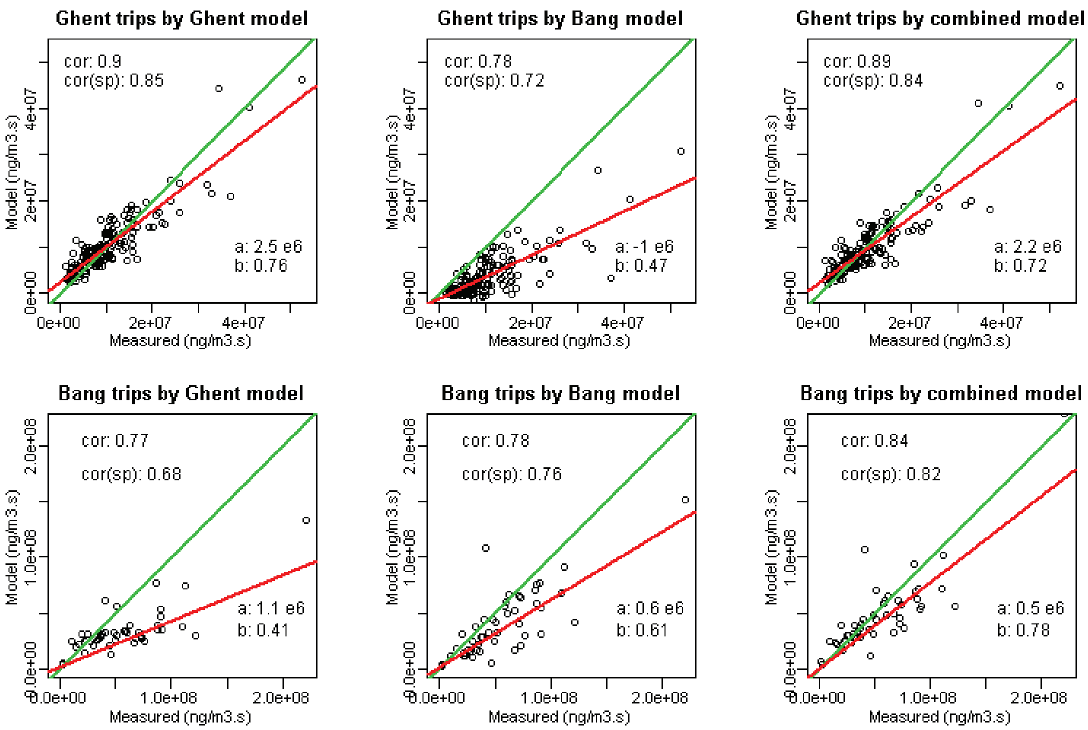

Figure 4 – Trip-based comparison and cross validation of the Ghent and Bangalore models. Each dot represents the total predicted exposure by trip compared to the measurement. The green line indicates the perfect fit; the red line presents the linear fit on the total trip exposure predictions. Correlations (Pearson and Spearman) and linear fit parameters of the trip prediction are shown for each plot.

3. FIXED NOISE AND AIR POLLUTION MEASUREMENTS

A fundamental feature of the mobile measurements is the possibility to disentangle the variability in the BC exposure into a local traffic component and a background component. This concept is now also tested in a pilot setup at a high exposed dwelling facade (2-Section 4.7). Six weeks of simultaneous measurements in various traffic situations and meteorological conditions are evaluated with different noise parameters and different background stations (see Table 1). The in-city background location does not result in the strongest model. A remote background location performs better due the fact that the remote location only adds meteorological influences in the model while the in-city background location adds both meteorological influences and in-city diurnal traffic pattern. The large-scale traffic influences in the in-city background measurement locations compete and sometimes conflict with the local traffic information provided through the noise measurement.

Different noise indicators are also compared. Two variants of engine noise related parameters are included ($L_{OLF,bike}$ and $L_{OLF,eq}$). The first parameter is an arithmetic average of the vehicle events, not conserving the acoustical energy, the second parameter is an acoustical energy conserving parameter providing the low frequency noise for the temporal resolution of the model ('15 minutes). The two parameters show a different behavior in the models. The energy conserving variant $L_{OLF,eq}$ is not always better compared to the L_{Aeq} or other statistical evaluations, especially in the model based on the remote background location. It illustrates the complexity of the correlation between traffic BCimmission and noise immission as well as the potential influence of other sound sources. . Simple and classical noise parameters -energy conserving or statistical levels- are not expected to improve the models. The traffic specific event-based parameter expresses more potential. This pilot study has to be extended to multiple dwellings. Variants of event-based noise parameters should be investigated as a fast and sensitive approach to include traffic data into air pollution models.

Background station	Noise parameter	Deviance explained	AIC	Intercept (ng/m3)	F-values				# samples
					log(BCbkg)	Wind speed	Tempera-ture	Noise parameter	
Remote background	LOLF,bike	28.8%	5290	1432	17	62	58	218	1961
Remote background	LAeq	28.6%	5299	1432	16	62	57	71	1961
Remote background	LA50	28.3%	5307	1432	16	60	59	72	1961
Remote background	LA05	28.2%	5310	1429	17	61	61	66	1961
Remote background	LA95	26.9%	5345	1430	18	60	64	54	1961
Near major city	LOLF,bike	26.2%	5688	1114	79	14	13	112	1961
Near major city	LA50	25.9%	5697	1114	78	14	14	109	1961
Near major city	LAeq	25.8%	5699	1113	79	15	15	108	1961
Remote background	LOLF,eq	25.1%	5393	1426	16	46	83	37	1961
Near major city	LA95	24.8%	5725	1110	77	12	17	96	1961
Near major city	LA05	23.1%	5769	1106	77	17	22	81	1961
Near major city	LOLF,eq	22.8%	5778	1110	72	4	26	78	1961
In-city park	LOLF,eq	21.2%	5359	1238	49	14	26	49	1961
In-city park	LOLF,bike	20.6%	5370	1237	56	23	20	131	1961
In-city park	LAeq	20.6%	5371	1236	56	23	23	130	1961
In-city park	LA50	20.6%	5371	1237	55	23	22	130	1961
In-city park	LA95	20.6%	5375	1238	51	21	18	43	1961
In-city park	LA05	20.0%	5389	1233	55	21	26	39	1961

Table 1 – Model variants with different noise parameters and different background measurement locations illustrate the potential of dwelling facade modeling using noise to include traffic variability. Close in-city background measurement locations do not improve model quality.

4. CONCLUSIONS

Despite the fundamental property of simultaneous emissions, the correlation between noise and particulate matter exposure is complex. The noise measurements contain spectral information that is highly relevant to improve this correlation and specific noise indicators could be derived for this purpose. Simultaneous noise and BC and UFP measurements add significant value to the quality of the air pollution models. It enables the disentanglement of the major driving forces of traffic related air pollution exposure: meteorological conditions, background concentrations and actual local traffic. The spectral evaluation adds information on the traffic dynamics and the traffic dynamics have strong impacts on the local BC and UFP emissions of the vehicle flow. That combination, quantifying the traffic dynamics through noise and the highly non-linear behavior of the BC emissions in dynamic traffic is responsible for the strength and stability of the derived models.

All noise assessments can be used for annoyance and direct noise related health impact research within the acoustic discipline, using the standard noise parameters. Specific BC related noise parameters improve the air pollution models. Important synergies will emerge when more long-term combined measurement campaigns of noise and air pollution campaigns are performed. Correlations with specific short-term noise parameters and air pollution might explain the exposure situations where the correlation between the standard noise exposure indicators and air pollution exposure breaks down.

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